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An Experimental Study On Real-Option Strategies

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An Experimental Study On Real-Option Strategies

Abstract

We conduct a laboratory experiment to study whether people intuitively use real-option strategies in a dynamic investment setting. The participants were asked to play the role of an oil manager and make production decisions in response to a simulated mean-reverting oil price. Using cluster analysis, participants can be classified into four groups which we label as “mean-reverting,” “Brownian motion real-option,” “Brownian motion myopic real-option,” and “ambiguous.” We find two behavioral biases in the strategies of our participants: ignorance the mean-reverting process, and myopic behavior. Both lead to overly frequent switches when compared with the theoretical benchmark. We also find that the last group behaved as if they had learned to incorporate the true underlying process into their decisions, and had improved their decisions during the later stage.

Keywords: Real Options, Experimental Economics, Heterogeneity.

JEL classification: C91, D84, G11

1 Introduction

In many capital budgeting scenarios, managers have the possibility to make strategic changes, such as postponement and abandonment, during the life of the project. A typical example is that of an oil company who may decide to temporarily shut down production when the oil price falls below the extraction cost, yet decide to start operation as soon as the oil price rises above the extraction cost. This happened during the Gulf war when several oil fields in Texas and Southern California began operations when the oil price increased sufficiently enough to cover the relatively high extraction cost (Harvey 1999).

Strategic options such as that above are known as real options because the real investment can be seen as coupled with a put or call option. Real-option research is one of the most fruitful fields in finance. Compared with the traditional Net Present Value (NPV) approach that offers an all-or-nothing answer to the investment decision, the real-option method takes advantage of wait-and-see and reacts strategically when uncertainty evolves over time. Investors can cut off unfavorable outcomes by considering the options of abandonment, deferment, switching. As a result, the real-option approach can substantially increase the value of a project, when compared with the less flexible NPV approach.

Complicated methods have been developed to evaluate a variety of real options. Yet, in reality, people can still make different kinds of mistakes by applying the model incorrectly, or misunderstanding the real-option nature of a particular project. Therefore it is crucial to know whether the real-option approach makes intuitive sense to investors, and if not, what are the possible pitfalls. For example, in the U.S. and other countries, the government regularly auctions off leases for offshore petroleum tracts of land. The oil company has to bid hundreds of millions of dollars on such tracts, thus it is important to perform valuations as accurately as possible. Given the magnitude of the stakes of such an investment, even a tiny valuation mistake may cause large financial losses. But as observed by Dixit & Pindyck (1994), even the government can arrive at valuations which are too low, if they apply the NPV instead of the real-option method.

Despite extensive theoretical work on real-option modeling, empirical testing of real options has nonetheless been scarce. In particular, we know very little about how people in the real world (e.g., managers) actually value real options more than at an anecdotal level. It is mainly due to the intrinsic difficulties in obtaining reliable data on components of the real-option approach, such as the current and future value of an underlying asset, and the investor's expectations of future cash flows. Previous empirical studies of real options often use either estimations or proxies for these input parameters

(e.g., Quigg, 1993). Such problems may be circumvented by using surveys or well-controlled experiments.

In this paper, we report a laboratory experiment on real-option decisions. Our participants were asked to imagine they are oil-field managers. The experiment lasts 100 periods. At the beginning of each period, the participants observed the oil price in a simulated market and had to decide on production technologies. Depending on the current status, they could decide whether to keep the current level of production, to increase or decrease the production by using different technologies, or to shut down the production temporally. All changes at the production level incur switching costs. A real-option strategy in this scenario would take into account the flexibility of investment decisions and switch less often than a NPV strategy. If we assume that the output price follows a Brownian motion process, then real-option strategies suggest that one should change less often towards the end of the game as switching costs would not compensate the expected potential profits.

The underlying process of output prices also has important implications regarding optimal strategies. For example, if the underlying price follows a mean-reverting process, then it can happen that both the NPV and the real-option strategy predict no or few changes of technologies. We will discuss the difference between the various processes in later sections.

The main contribution of this paper is that it is the first exploratory study on the heterogeneity of intuitive real-option strategies in a continuous-time setting. The underlying stochastic process of output price is determined by the experimenter. The real-option strategies can be calculated under different assumptions of the price process and risk attitude. The models are flexible enough to fit the observed behavior, and to accommodate different types of investors.

The advantage of using an experimental method is that we can control the underlying price process and compute the optimal investment strategies based on various theoretical assumptions. The behavior of the participants can then be compared with theoretical benchmarks, and we can identify different groups based on their implicit strategies. Using cluster analysis, we identify four typical strategies used by the participants, labeled as “Mean-reverting,” “Brownian motion real-option,” “Brownian motion myopic real-option,” and “ambiguous.”

Only nine out of our 66 participants belong to the “mean-reverting” group who changed least often and earned the highest average profit among all four groups. Our calculation shows that when assuming a mean-reverting price process, it is optimal to stay at the current production level, regardless of whether one applies a real-option or NPV strategy. “Wait-and-see” has the highest value in this case.

Twelve participants are clustered into the “Brownian motion real-option” group. The modal behavior of this group resembles a real-option strategy when assuming a Brownian motion price process and risk aversion. Investors switch to high-production technology when the price is sufficiently high and shut down production when the price is too low. During the later periods, however, it is no longer worth switching as potential profits are limited.

The biggest group in our cluster analysis is labeled the “Brownian motion myopic real-option” group, and contains nearly half of the participants (29 out of 66). They behave as if they follow a real-option strategy assuming a Brownian motion process with risk-aversion, yet without considering the limited time horizon of the game. In other words, they play as if the game would last forever and thus change too frequently at the end of the game.

The strategies of the remaining 16 participants are rather ambiguous. During the first 67 steps, their strategies are more similar to real-option strategies with a Brownian motion process, whereas during the last 33 steps, their switching behavior fits best with the NPV or real option strategy under the assumption of a mean-reverting process.

It seems that the majority of our participants play as if they believe in a Brownian motion process, whereas the true process we used in this experiment is a mean-reverting process. A natural question to be asked is how the price process perceived by the participants? For each period we therefore elicited the participant’s price expectation for the next period. Interestingly, it seems that the perceived process is more similar to a mean-reverting underlying price process. However, most participants behave as if they are not aware of this process, or do not incorporate this information into their decisions.

Some theorists observe that the intuitive investment decisions by managers are closer to real option strategies than the traditional NPV strategy (Dixit & Pindyck 1994). Our results seem to support this observation as the NPV strategy does not capture the behavior of most participants. However, we find two typical behavioral biases from our participants. First, many participants do not take into account the finite time horizon and switch too often at the end of the game thereby reducing their earned profits. Second, although many participants expect a mean-reverting price process, they react to the price movement as if the price followed a random walk leading to overly frequent switches.

Despite certain behavioral biases, some participants demonstrate a specific kind of learning effect during the experiment. Two ways of learning are possible. The first way of learning is to increasingly behave according to the real-option strategies over time. The behavior of the “Brownian motion real-option” group, for example, fits better with the corresponding strategies at

later stages of the experiment. The second way of learning is to perceive the true underlying mean-reverting process, and to incorporate this process into decision making. The last group (i.e., "ambiguous" strategy), for example, behaves as if they have learned to incorporate the mean-reverting process into decisions made during the later stage.

The structure of the rest of the paper is as follows: in the second section we review the relevant literature on empirical and experimental real-option studies. In the third section we outline the theoretical framework behind our experimental design. The fourth section describes the experiment procedure and the results. In the last section we discuss the theoretical and practical implications of our study.

2 Literature Review

Before the formal introduction of the theoretical real-option technique, many corporate managers and strategists dealt with the ideas of managerial flexibility and strategic interactions on an intuitive basis. Dean (1951), Hayes & Abernathy (1980) as well as Hayes & Garvin (1982) recognized that the standard Discounted Cash Flow (DCF) criteria often undervalue investment opportunities. This would lead to myopic decisions, underinvestment and eventual losses of competitive positions because important strategic considerations are either ignored or not properly valued. Myers (1977) first proposed the idea of thinking of discretionary investment opportunities as growth options. Kester (1984) discussed the strategic and competitive aspects of growth opportunities from a conceptual point of view. Other general aspects of real-option framework have been developed by Mason & Mer-ton (1985), Trigeorgis & Mason (1987), Trigeorgis (1988), Brealey & Myers (1991), Kulatilaka (1988) and Kulatilaka (1992). More specific applications of the real-option framework to various investment problems include real estate development (Titman 1985, Williams 1991), lease contracts (Schallheim & McConnell 1983, Grenadier 1995), oil exploration (Paddock, Siegel & Smith 1988), and research and development (Dasgupta & Stiglitz 1980).

To our knowledge, there are very few experimental studies on real options. The findings are somewhat mixed regarding whether people's intuition is consistent with the real-option theory. For example, there is evidence that the subjects make less irreversible investment now if they expect more information about the risky asset to surface in the future (Rauchs & Willinger 1996). Howell & Jägle (1997) asked managers to make hypothetical decisions on investment case studies in the context of growth options. In their setting, after a fixed period of time, it is possible to invest in a follow-up project. Several

factors in the Black-Scholes model, such as Present Value, volatility and time to maturity, have been varied to investigate whether respondents could intuitively apply a real-option approach. Although it seems that the respondents did not hold the simplistic NPV view for valuation, their decisions were not perfectly in line with the real-option theory, neither. Both under- and overvaluations occur. It has also been observed that factors such as industry, sector, personal experience and position influence valuations. Interestingly, more experienced managers were more likely to overvalue the projects, probably due to overoptimism. In general, the respondents behavior cannot be described by one model due to the existant heterogeneity.

Another notable experimental study is from Yavas & Sirmans (2005), who applied a simple two-stage investment setting to test for optimal timing by the subjects. They also measured the premium associated with the real-option components of an investment and examined how this premium is correlated with uncertainty about future cash flows from the investment. Their results again provide mixed evidence regarding the descriptive validity of real-option theory. On the one hand, most subjects seemed to be too optimistic and entered the project too early when compared with the theoretical optimal timing. On the other hand, in the bidding experiment, their bids for the right to invest in a project were generally close to the theoretical level, and reflected the value of the real option embedded in the project. Moreover, the bidding behavior of the participants was consistent with the option pricing theory, which predicts that greater uncertainty about future cash flows increases the value of the project.

An interesting phenomenon in the Yavas & Sirmans (2005) experiment is the learning effect. At the beginning, the bids were too optimistic and hence too high, which is consistent with the typical observation that inexperienced investors tend to be more aggressive and optimistic. The price, however, converges with the theoretical predictions as their experience increased. There was also evidence that some subjects, with experience, learned to postpone their investment decisions in order to make more optimal decisions.

In an option pricing experiment, Abbink & Rockenbach (2006) found that students with technical training in option pricing were better at exploiting arbitrage opportunities than professional traders and students without formal training. Miller & Shapira (2004) have used hypothetical questions on real option pricing and identified certain biases that are consistent with behavioral decision theory.

While the above studies are among the first empirical tests of option pricing theory, their set-ups are relatively simple. Subjects typically only make decisions over no more than three periods. Although simplified tasks help to disentangle confounding factors, it is not clear whether one can gener-

alize the results to the more realistic context. This motivates us to start an experiment on real-option investment in a highly dynamic environment, which is more complicated but also more realistic. Consistent with previous observations, we find real-option strategies seem to be more intuitive than the NPV approach, but that people differ very much in their strategies. We can categorize the subjects into four typical types. The behavior of some groups is consistent with some previous findings such as the learning effect and myopic behavior.

3 Theoretical Model

As a starting point, we established the theoretical framework for an oil-manager investment game in which players are supposed to choose among various oil-production technologies in a dynamic market setting in order to maximize their profits. In our setting, it is assumed that the exploration and development of the oil field have been completed, and the manager only encounters the decisions during the extraction stage. We have designed the exogenous underlying price process, and solved the optimal strategies as well as the optimal timing, accordingly.

3.1 NPV vs. Real Options

Since for each period, players can make production decisions as a response to the current market price, the situation is comparable to a series of American call-options that can be exercised any time before the expiration date. The real-option approach can be applied in this scenario and is different from the traditional NPV approach in that it has the advantage of waiting. When using NPV as the criterion to evaluate the investment opportunity, one should invest immediately as long as the project has a positive Net Present Value. In comparison, the real-option theory prescribes that it is sometimes better to wait until uncertainty regarding future cash flows is resolved. We calculated the optimal timing and the investment strategies for both the NPV and the real-option approach as our theoretical benchmarks, as explained below.

3.2 Geometric Brownian Motion Process

Geometric Brownian motion is among the most common continuous-time stochastic processes to model prices. A stochastic process P_t is said to follow a Geometric Brownian motion if it satisfies the following equation:

$$dP_t = \mu P_t dt + \sigma P_t dW_t \quad (1)$$

where $\{W_t, t \geq 0\}$ is a Wiener process or Brownian motion, and the constant parameter σ represents variance or volatility. In our setting, the drift μ is equal to zero. The increments in P , i.e., $\Delta P/P$, are normally distributed, which means that absolute changes in P , i.e., ΔP , are lognormally distributed, which is why the process has the name “geometric.”

The following set defines the possible critical prices S_{crit} where it is reasonable to change the technology (see Appendix A for the proof):

$$\left\{ \frac{-\frac{\alpha I}{T-u} + Q_{old}C_{old} - Q_{new}C_{new}}{Q_{old} - Q_{new}} \middle| u \in [t, T], \alpha \geq 1 \right\} \quad (2)$$

where Q denotes the quantity of production (e.g., the number of barrels of oil produced), and C denotes the cost per unit (e.g., cost per barrel). The subscript *old* refers to the adopted technology at a given time period t . The subscript *new* stands for all possible technologies other than the status quo. The numerator is a sum of two parts: the first part is the investment cost I multiplied by a factor α and divided by the remaining time steps $T - t$, in which T is the number of total periods and t is the current period; the second part is the difference between the total production cost of the old and new technology. The denominator is the difference in production quantity between the current technology and the alternative technology.

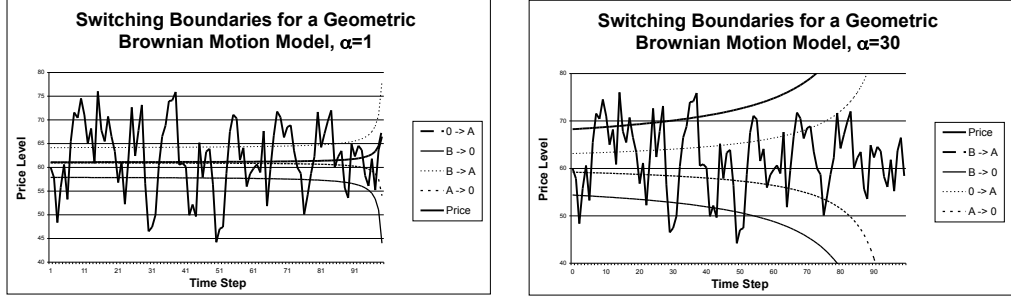
The real option strategy takes into account future uncertainty and reevaluates the investment cost. That is, the investment cost I is multiplied by parameter α , which reflects to which extent to the investor considers the future uncertainty. The larger the α , the longer the player waits before switching. When $\alpha = 1$, it is equivalent to the NPV strategy. When $\alpha > 1$, it corresponds to a possible real-option strategy.

Figure 1 suggests such boundary solutions for a Geometric Brownian motion process. It shows the fluctuating price process and the switching boundaries that symbolize the critical price S_{crit} , where it is rational to switch from one production condition to another. The left panel indicates the solution for the NPV strategy $\alpha = 1$ and the right panel shows the boundaries for the optimal real option strategy with $\alpha = 30$. Compared to the real-option strategy, it is clear that the NPV strategy boundaries are much narrower, triggering more frequent switches between production levels.

In our experimental setting, when assuming a Geometric Brownian process, a player would change technologies 38 times according to the NPV approach. It would cost \$12,300 for technology changes, which almost offset the gross profit of \$14,071, resulting in a net profit of \$1,771. In comparison, if an investor adopts the optimal real option strategy with $\alpha = 30$, which theoretically leads to maximum profits, then one only needs to change tech-

nologies 17 times. The net profit increases from \$1,771 to \$4,689, due to the reduction of switching costs.

Figure 1: Switching boundaries for an NPV strategy ($\alpha = 1$, left panel) and a real-option strategy ($\alpha = 30$, right panel) with a Geometric Brownian Motion price process:



Notes: “A” denotes technology A, the technology with high production level and high cost; “B” denotes technology B, the technology with low production level and low cost; “0” denotes no production. “X → Y” denotes switching from production X to production Y.

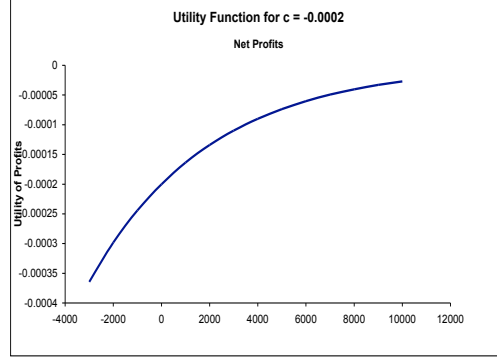
Another characteristic of the boundaries for the NPV strategy is that they are almost flat for the first ninety periods, and only spread at the very end. This means that players should stop switching around the last ten periods as switching costs are too high compared to the limited expected profits. In comparison, the boundaries for the real-option strategy spread out even earlier, implying that it is optimal to stop switching during the second half of the game.

3.3 Risk Aversion and Mean Reversion

We now look at the boundary solutions for the more realistic assumptions, namely risk-averse attitude and mean-reverting process. Most real-option models assume investors are risk-neutral, but in reality most investors are risk-averse. We can assume an exponential utility to capture the degree of risk-aversion as follows:

$$u(x) = ce^{cx} \quad (3)$$

where c is the risk-aversion coefficient. Figure 2 shows a typical exponential utility function with $c = -0.0002$, which seems to fit the behavior of some types of our participants, as we will show later.

Figure 2: Exponential utility function ($c = -0.0002$)

Moreover, although a Geometric Brownian motion as described above is frequently used to model economic and financial variables such as interest rates and security prices, one may argue that it is more likely that in practice oil prices follow a mean-reverting price. As Lund (1993) points out, Geometric Brownian motion is hardly an equilibrium price process. The reason for this is that when prices rise, there are incentives for existing firms to increase production and for new firms to enter the market. The natural consequence is that the larger supply would slow down the price increase ultimately causing prices to decline. The same logic applies in the case of price decrease. Therefore, at the market level, a mean-reverting process is a more plausible process for oil prices and has been supported by some empirical tests (see e.g., Pindyck & Rubinfeld (1991)).

In our experiment, a mean-reverting process is used to model the stochastic behavior of the continuous-time oil prices. The oil price P at time t is:

$$P_t = P_t^D e^{k(-\frac{Q_t^{tot}}{Q_{h,t}^{max,tot}} + 0.5)} \quad (4)$$

The above pricing process has two components, a mean-reverting component and an exponential one. The first component P_t^D follows a mean-reverting, or Orstein-Uhlenbeck process with:

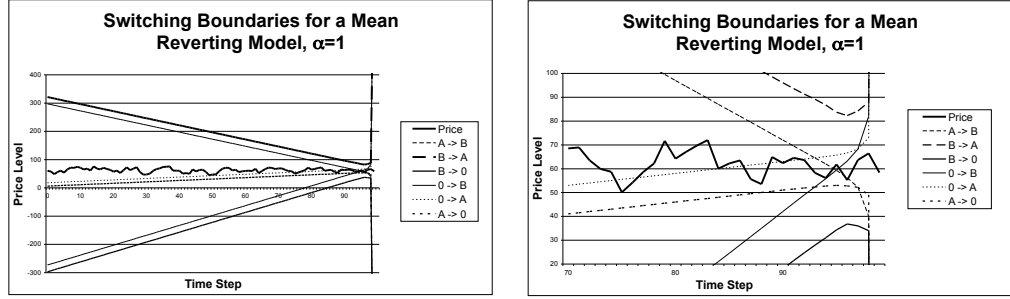
$$dP_t^D = h(\mu - P_t^D)dt + \sigma dW_t \quad (5)$$

where W_t (for $t \geq 0$) is a Wiener process or Brownian motion, μ is the long-run mean of P_t^D , h is the speed of adjustment, and σ models the volatility

of the process. In our experiment, $\mu = 61.5$, $h = 0.5$, $\sigma = 9.07$, and $k = 0$.

The second component in Equation 4 – the exponential function – models the supply side. The fraction in the exponent measures production, which is the ratio between realized industry production (Q_t^{tot}) and maximum industry production where all firms had chosen technology with the highest capacity ($Q_t^{max,tot}$). The fraction has a co-domain of $[0,1]$. k is a constant factor that determines the impact of the exponential on P_t^D . It is a proxy for the market size of the managed oil fields relative to the total market size. The higher the k , the bigger the impact of supply on price. When $k = 0$, the oil price P_t is determined independent of the oil production decisions by the market participants, which is the case in our experiment.

Figure 3: Switching boundaries for NPV strategy with a mean-reverting price process (Left panel: all 100 time steps; Right panel: step 70 to 100) $c=-0.0002$:



Notes: The left panel shows the boundary solutions for the entire session (period 1 ~ 100). The right panel shows the boundary solutions from period 70 to 100, so one can see in more detail the solutions towards the end of the experiment. “A” denotes technology A, the technology with high production level and high cost; “B” denotes technology B, the technology with low production level and low cost; “0” denotes no production. “X → Y” denotes switching from production X to production Y.

Appendix A provides the proof for the boundary solutions. Figure 3 shows the switching boundaries of an NPV strategy (i.e., $\alpha = 1$) for the mean-reverting price process. The left panel shows the switching boundaries for all 100 time periods, whereas the right panel shows the boundaries for the last 30 periods, so that one can see in more detail the boundaries towards the end. The boundaries become narrower over time but spread at the very end (the right panel). Indeed, with a mean-reverting process there are fewer incentives to change technology as the process is expected to revert to its equilibrium level and the expected profit generated by a change of technology

could be negative. However, as time goes by, if the speed of adjustment is not too fast, the realized profit could be substantial as the price is expected to be much higher than the equilibrium level at maturity. Finally, when close to maturity, the sunk cost generated by a switch of technology is not compensated by possible profit. The boundaries spread at the very end as it does not make sense to change technology at that time. For any prices between the two boundaries $B \rightarrow A$ and $B \rightarrow 0$ the expected price will rapidly converge towards the mean price. For the mean price, technology B is the most profitable strategy, even for an NPV strategy ($\alpha = 1$). For this reason, in our setting one should never change production technologies if he/she assumes a mean-reverting process, regardless of whether he/she adopts an NPV or a real-option strategy.

3.4 Brownian Motion (BM)

When the speed of adjustment h is equal to 0 in Equation 5, the process is consistent with a Brownian motion process. It can be considered to be a continuous-time version of a random walk. It has the Markov property in that the past pattern of prices has no forecasting value, often referred to as “the weak form of market efficiency.” It is based on the theoretical assumption that all public information is quickly incorporated into the current price and hence, no investors can “beat the market.”

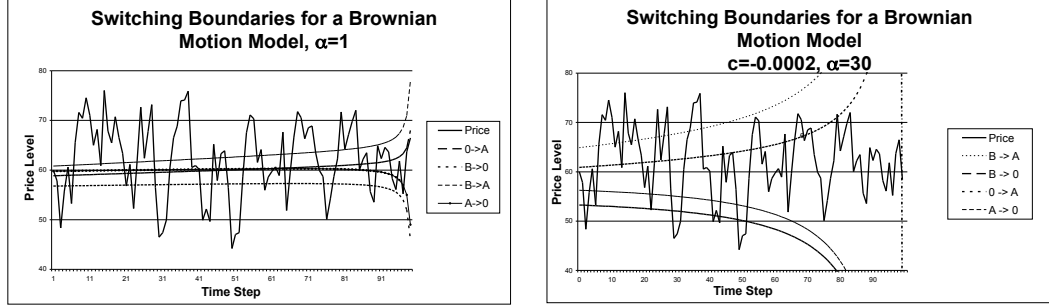
Compared with the mean-reverting processes, the decision rules for Brownian motions are more explicit and intuitive. In principle, investors should start or increase production when the price rises above some threshold, and stop or reduce production when the price falls sufficiently. Figure 4 shows the boundaries for NPV and a real option strategy when $c = -0.0002$ in the exponential utility function (Equation 3). See Appendix A for the proof.

4 Experiment

4.1 Participants and Procedure

In total seventy-one undergraduate students from the University of Zurich in Switzerland participated the experiment in June 2007. The subjects were recruited from classes in economics or finance. In the experiment, they were asked to play the role of an oil-field manager and to run the oil field to maximize profits. For this purpose, they had to produce and sell oil in a simulated market. Their earnings were based on the oil price, which was generated from a mean-reverting Markov process specified in Equation 4

Figure 4: Switching boundaries for real-option strategy with a Brownian price process and risk-aversion attitudes ($c=-0.0002$) (Left panel: NPV $\alpha = 1$; Right panel: Real Option $\alpha = 30$):



Notes: “A” denotes technology A, the technology with high production level and high cost; “B” denotes technology B, the technology with low production level and low cost; “0” denotes no production. “X → Y” denotes switching from production X to production Y.

and Equation 5 in the section of theoretical models. The price process is exogenous and the players are price takers, since we are mainly interested in investors’ strategies, not market equilibrium. The experimental session lasted 100 periods. Each period represents one business day and is divided into 10 sub-steps simulating the development of the oil price during the day. For simplicity, the oil cannot be reserved for the following periods, and all oil produced is automatically sold at the end of each period. The players were asked to choose from two production technologies for the next period: (1) Technology A has a higher production level (50 barrels per day) and higher cost (\$61¹ per barrel); (2) Technology B has a lower production level (25 barrels per day) and lower cost (\$58 per barrel). Alternatively, a player could also choose to disinvest or shut down production, resulting in zero production level. Switching between different technologies, or switching from zero level to a new technology costs \$350 each time, whereas switching between existing technology and disinvestment costs \$300 each time. The whole experiment took about one hour and included an introduction, an experimental and a questionnaire session. The average earnings per participant was 33.50 CHF (SD=12.90 CHF).

The simulation also generated messages about the incoming price movement. There are three treatments regarding incoming messages: (1) Filtered information: participants only received messages that are relevant to the

¹The symbol \$ here represents experimental currency.

price movement; (2) Full information: participants received a mixture of relevant and irrelevant messages regarding the price movement; (3) No information: participants received no information.

4.2 Classification of participants based on strategies

As the data for five participants were excluded due to invalid answers, there were 66 participants in the final analysis. In order to classify participants based on their switching decisions, we ran a two-step cluster analysis for all participants with all 100 periods. A two-step cluster method is a scalable cluster analysis algorithm to handle very large data sets. Unlike the K-means or hierarchical clustering, the two-step cluster method can handle both continuous and categorical variables. In our case, since the decision variables are categorical variables, the two-step cluster method is the only appropriate method. The log-likelihood distance measure and BIC criterion were used to detect the optimal number of clusters. The cluster analysis revealed four homogenous subgroups which can be compared with candidate theoretical strategies.

Now let us look at the matching rate with the candidate strategies for each subgroup in Table 1. Each column represents one of the six potential strategies that have been discussed in the theoretical section, while each row represents one of the four types of investors from the cluster analysis. We compare the modal behavior of each cluster with the theoretical strategies. The matching rate is defined as the percentage of decisions which coincides with the theoretical strategies for all 100 periods. It seems that the first group matches very well (matching rate=0.94) with a NPV or real-option strategy when assuming a mean-reverting process.² We label this group as “mean-reverting.” The second group matches best with the optimal real-option strategy under the Brownian motion process with risk-averse attitude (matching rate=0.87). Thus they are labeled as “Brownian motion real-option.” The third group, labeled as “Brownian motion myopic real-option,” fits best with a myopic real-option strategy with risk-averse attitude. The last group is most similar to the NPV strategy with a Geometric Brownian motion process. However, later we will see that the last group behaves as if they changed the perceived price process from Brownian motion to a mean-reverting process. So it seems that this group did not follow a consistent strategy. Accordingly, we label them as “ambiguous.” We explain these four strategies in more detail below.

²Note that when assuming the mean-reverting process, both NPV and real-option strategies would prescribe no changes and staying in Technology B. See discussion in

Table 1: Matching rates for each group with different strategies

Group	N	Risk-averse attitude					
		Geo. Brownian NPV	Brownian RO	Mean-revert. RO/NPV	Brownian motion		
1. Mean-reverting	9	0.47	0.08	0.94	0.26	0.08	0.08
2. BM Risk-averse RO	12	0.39	0.71	0.08	0.53	0.87	0.73
3. BM Myopic RO	29	0.46	0.73	0.07	0.55	0.67	0.75
4. Ambiguous	16	0.58	0.49	0.45	0.49	0.50	0.50

Note: RO means Real Options and NPV means Net Present Value. Each row represents one of the four classified groups. Each column represents the potential strategies. Matching rate is the percentage of decisions that coincides with the theoretical strategies for all 100 periods for each group. For example, in the first row, 0.86 means that on average there are 86 out of 100 periods in which the decisions by participants in the mean-reverting group coincide with the theoretical predictions of NPV/Real option strategy for the mean-reverting price process. The bold fonts represent the highest matching rate among all theoretical strategies for a given group.

Figure 5 shows the majority behavior for each classified group as compared with the predicted decisions of the corresponding theoretical strategies. In the first row, the left panel shows the majority behavior for the “mean-reverting” group. Most of the time, technology B (low production technology) is chosen and coincides with the theoretical NPV or real option strategies when assuming the mean-reverting process (the right panel of the first row in Figure 5).

In the second row of Figure 5, the left panel shows that the majority of the second group, the so-called “Brownian motion real-option” group, switches between high production technology (Technology A) and no production during the first half of the game, but chooses the high production strategy (Technology A) during the second half of the game. This behavior pattern is very similar to a real-option strategy with $\alpha = 30$ under the assumption of Brownian motion price process and risk-aversion exponential utility function with the risk coefficient $c = -0.0002$ (see the right panel in the second row).

The majority behavior of the third group is shown in the left panel of the third row of Figure 5. As we can see from the graph, most of the time the participants switch between high production technology (Technology A) and no production. This behavior is similar to the second group during the

the theoretical section.

first half of the experiment. The difference is that the second group stops switching during the second half of the game, whereas the third group still keeps changing technologies, which is not optimal due to the high switching costs. This group behaves as if they do not consider the limited horizon of the game, and plays as if the game would last forever without a potential profits limit. In this case, the theoretical switching boundaries are not sensitive to the termination date and remain flat until the last period. They play as if they have adopted a “myopic real-option” strategy assuming a Brownian motion process.

The last group switches among both high production technology, low production technology, and no production (the left panel of the last row of Figure 5). In the last 10~15 periods, low production technology is chosen and no more switching occurs. This behavior is to some extent similar to a NPV strategy under a Geometric Brownian motion process. We label this group as “ambiguous”, because participants do not play consistently with one strategy. In contrast, they seem to learn the underlying price process and change their strategies over time. This will again be discussed in the section on the learning effect.

In summary, the behavior of the first two groups was closest to the rational real-option strategy under different assumptions of price process (mean-reverting vs. Brownian motions). The last two groups employed less optimal strategies thereby differentiating themselves from the first two groups in that they kept switching technologies towards the end of the game. The third group behaved myopically without considering the termination of the game. Although it was not consistent in its strategies, the last group, behaved as if it had learned the true underlying mean-reverting prices process. Table 2 shows that the first two groups switched less often than the last two groups, which corresponds to the theoretical predictions. Accordingly, the first group (“mean-reverting”) earned the highest profit on average, followed by the second group (“Brownian motion real-option”). The last two groups (“Brownian motion myopic real-option” and “ambiguous”) earned much lower profits.

4.3 Learning

In the above we analyzed the matching rates for the whole experiment for all 100 periods. Yet, it may be that the participants learned to play more optimally over time. We divided the 100 periods into three windows – periods 1-33, 34-67, and 68-100. Figure 6 shows that in some cases the matching rates indeed change dramatically over time. Decisions made by the second group match the “Brownian motion real option” strategy by approximately 80% for the first 33 periods, with the matching rate increasing to approximately

Figure 5: Classifying participants into four groups and the corresponding theoretical strategies

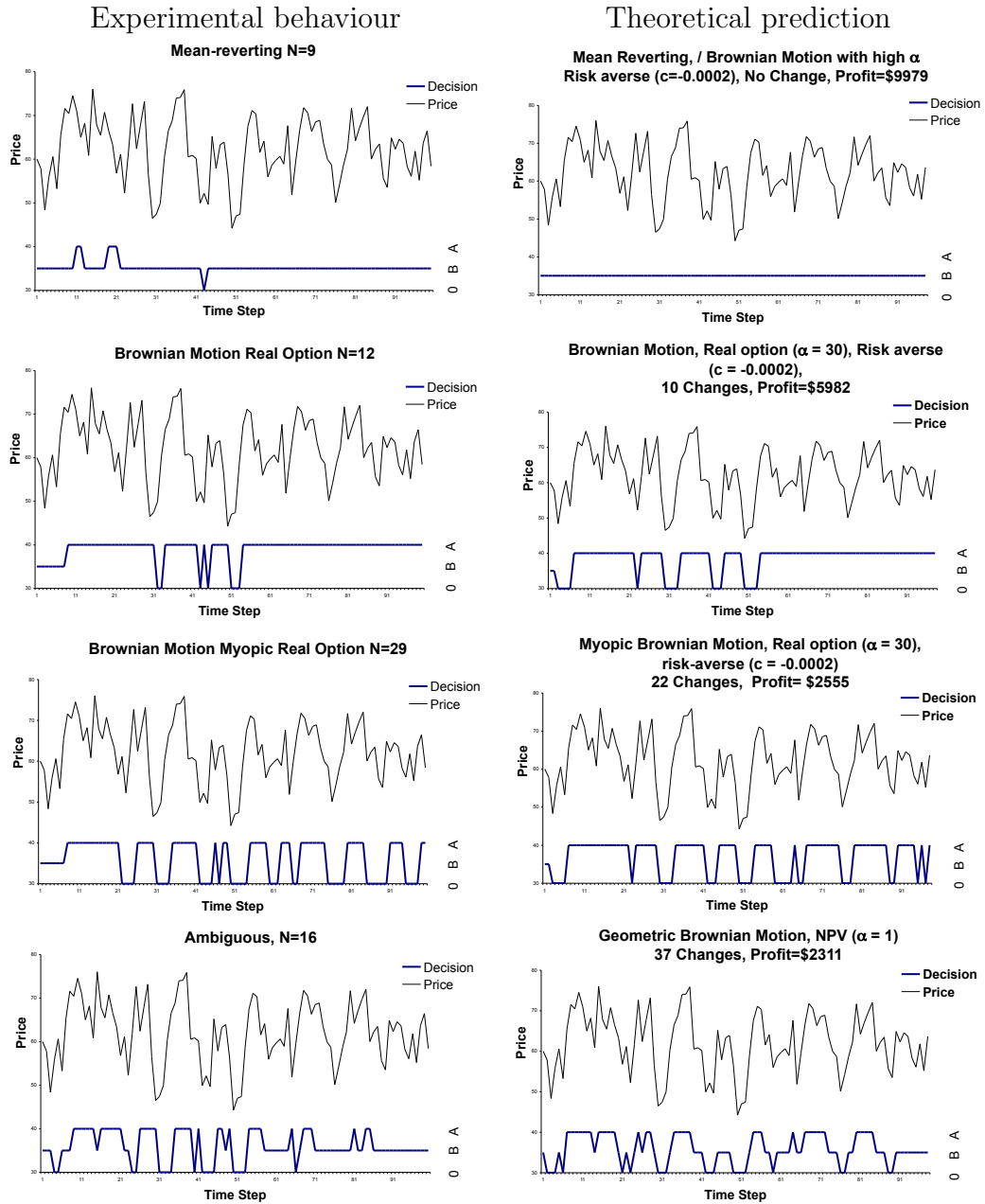


Table 2: Switching frequencies and average profits by each group

Group	N	Switching Frequencies		Mean Profit (\$)	
		Theoretical prediction	In experiment Mean(SD)	Theoretical prediction	In experiment Mean(SD)
Mean-reverting	9	0	9 (6.6)	9979	7076 (1909)
Brownian motion RO	12	10	10 (6.0)	5982	4750 (2383)
Brownian motion myopic RO	29	22	21 (5.3)	2555	3924 (2390)
Ambiguous	16	37	20 (9.6)	2311	3211 (2863)

95% for the last 33 periods. We can say, therefore, that this group appears to have learned to choose optimal strategies as time went on.

The group with an “ambiguous” strategy matches best with the real options strategy with Brownian or Geometric Brownian motion. However, in the last period, the matching rate of these two strategies drops sharply, and there is a dramatic increase in the matching rate of strategies with a mean-reverting process. They behaved as if they had identified the true underlying process, and had incorporated this information into their decisions later in the game.

The biggest group, the “Brownian motion myopic real-option” group, coincides best with the myopic real option strategy, without significant differences across three time windows. This group switched between technologies until the end of the game, which is non-optimal.

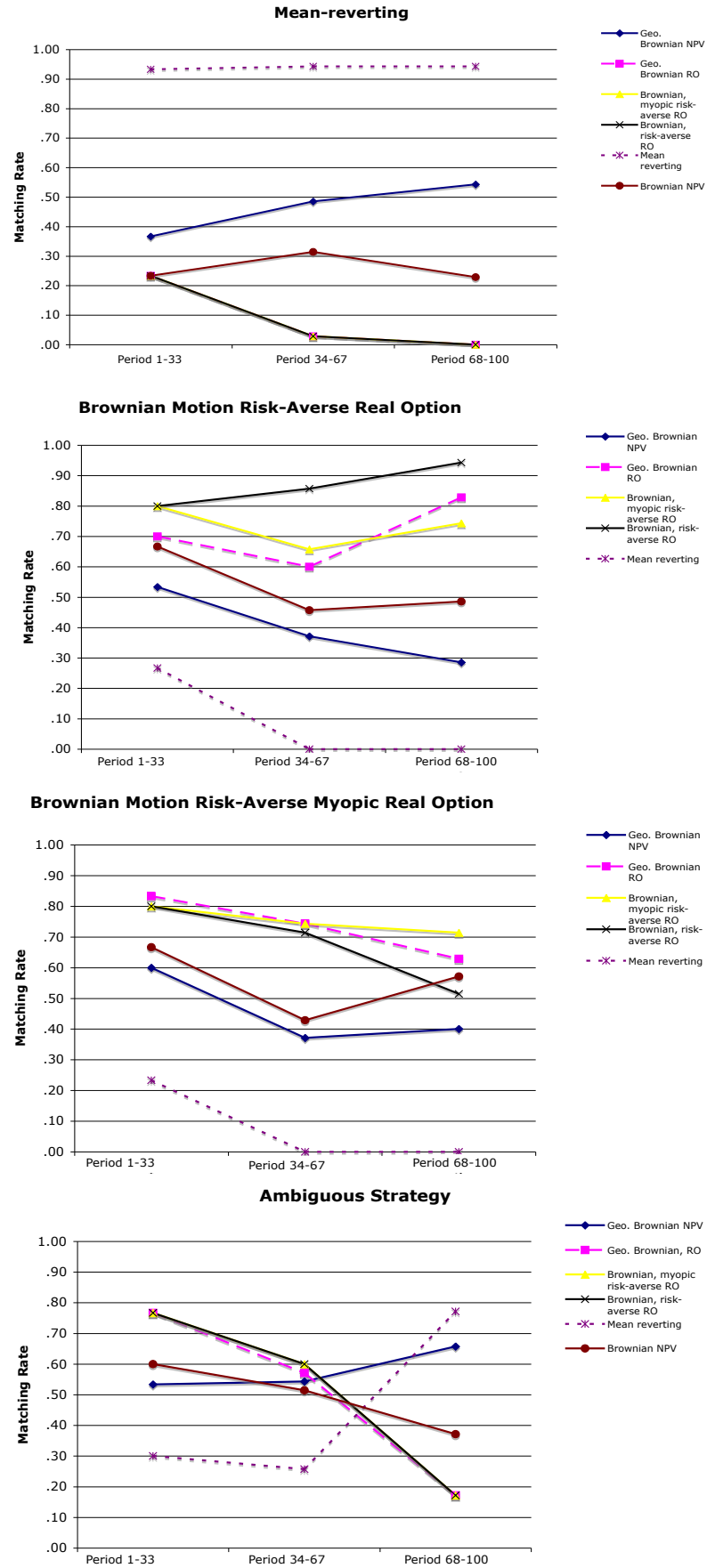
4.4 Expectations and decisions

Although the true underlying price process in our experiment was a mean-reverting process, the participants may have different perceptions. During the experiment, for each period we asked participants about their expectations regarding the price movement in the next period, which allowed us to check the expected price process.

Figure 7 compares the price prediction with past period prices for all four groups. It is interesting to see that all four groups perceived some kind of mean-reverting underlying price process—when the price in the previous period is high (low), they expected the price to go down (up) in the next period. For the middle-range prices, they expected little change in the next period.

This is puzzling because according to our comparisons with the theoretical

Figure 6: Matching strategies over time for four groups



strategies, most participants behaved “as if” they believed in a Brownian motion price process, but they seemed to perceive a mean-reverting process based on our elicitation of their expectations. In other words, they somehow expected the future price to revert to the average price, but they did not incorporate this information into their decisions. Instead, the participants switched production technologies as an immediate response to market price fluctuation. Figure 8 shows that in general, for high prices, they tended to use high production technology; for medium prices, they tended to use low production technology. When prices were sufficiently low, they tended to close down production. This contradicts the normative point of view. If investors believed the price would revert to some mean price, they should have waited more and should not have changed technologies so often, since potential profits would be too low to compensate switching costs.

4.5 Impact of information

In this section, we would like to examine the impact of information on price perception, strategies, and profits. Figure 9 shows the range of past period price as compared to price prediction for different information conditions. As expected, the group with no information perceives the price process to be close to a Brownian motion process, whereas the groups with filtered information and unfiltered information perceive the price to be closer to the true price process (mean-reverting process).

No significant differences were found between the group with filtered information vs. the group with unfiltered information. Therefore, we pooled these two groups with information, and compared them with the group without information. Figure 10 shows that the subjects with information were more likely to choose more profitable strategies, and belong to the “mean-reverting” and “Brownian motion real-option” groups. On the contrary, subjects without information were more likely to be classified into the last two groups (“Brownian motion myopic real-option” and “ambiguous”), who followed less optimal strategies. As a result, the group with information earned significantly higher profits than the group without information. Yet, there is no significant difference in switching frequencies between the group with information and the group without information (see Table 3).

5 Conclusion

This paper reports an laboratory experiment to test how people intuitively handle option-like investment. It can be seen as an extension of previous

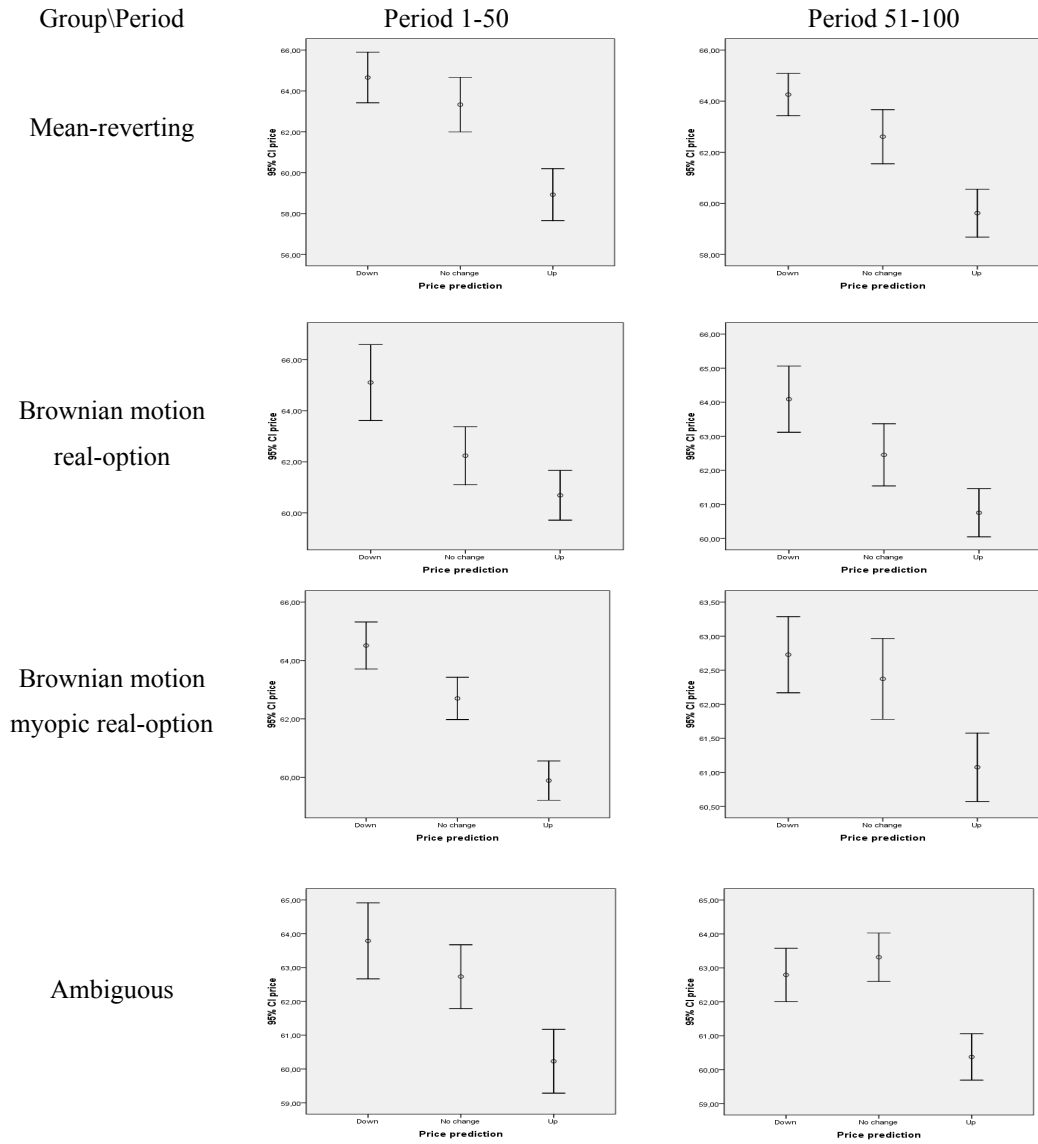


Figure 7: Price prediction vs. past price for all four groups

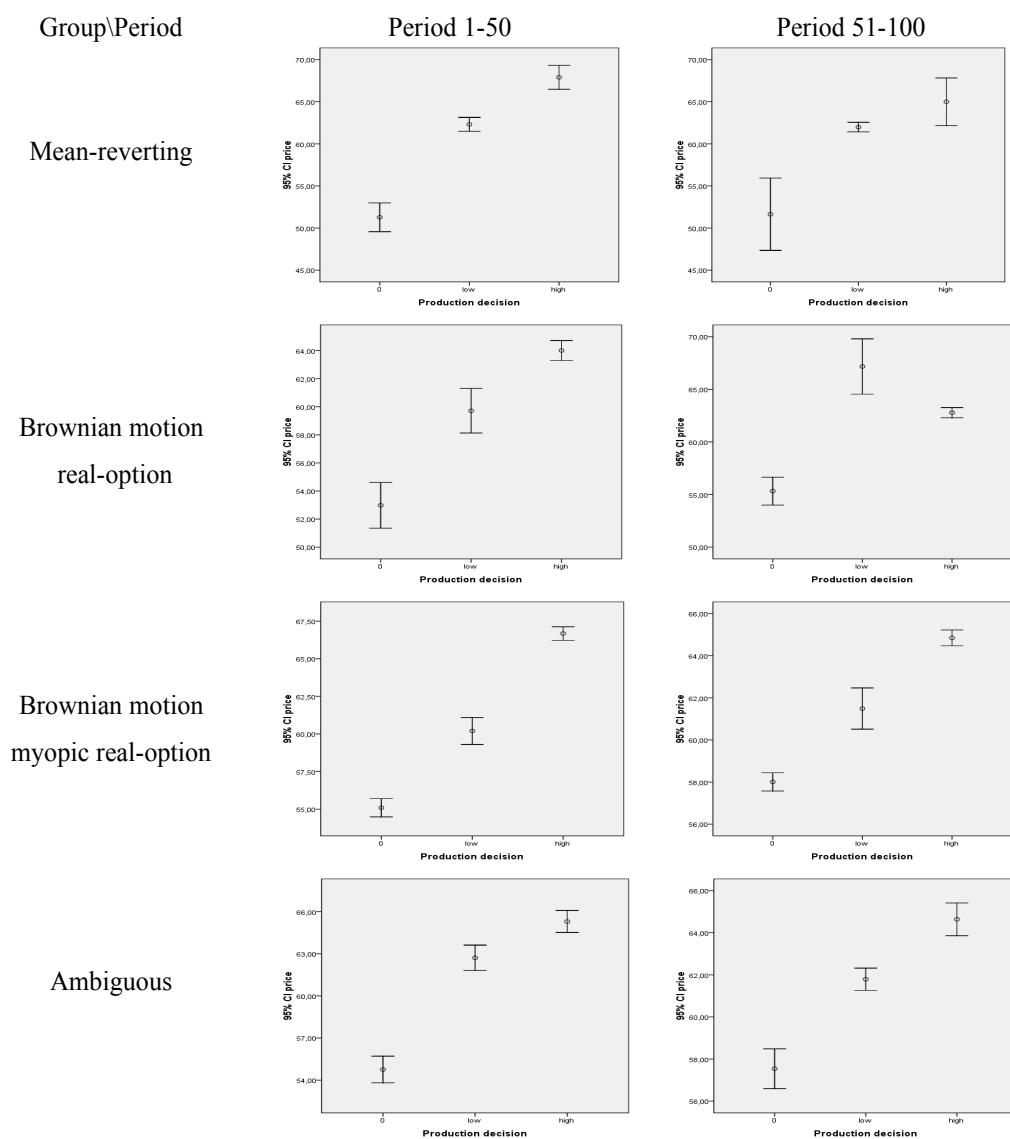


Figure 8: Production decision vs. past period price for all four groups

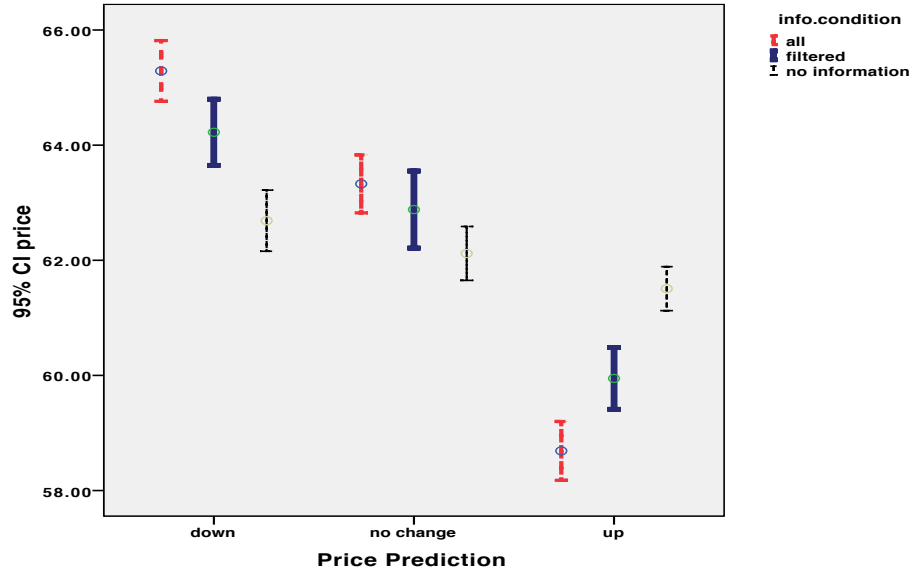


Figure 9: Price predictions vs. past period price across different information conditions

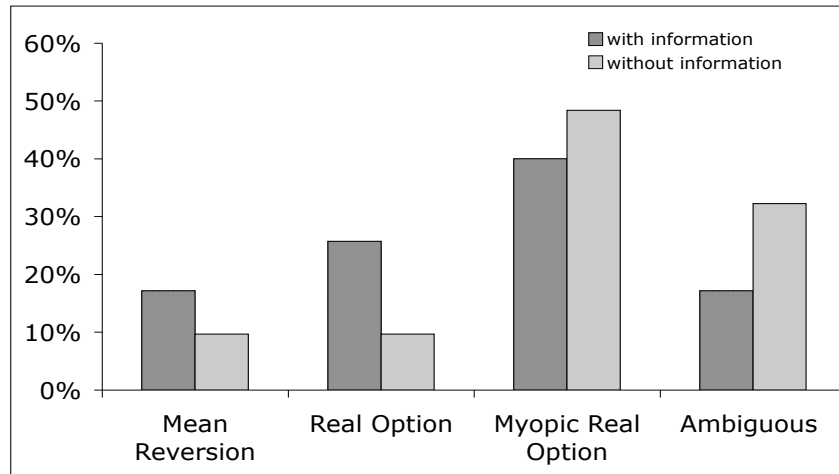


Figure 10: Group classification within information conditions

Note: The difference between full information and filtered information conditions is not significant. Therefore we pool these two groups and label it as "with information."

Table 3: Switching frequencies and profits by information treatment

Information treatment	With information Mean (SD)	Without information Mean (SD)	t-statistic	p
Switching frequencies	15 (9.3)	19(7.0)	-1.52	0.13
Profit (\$)	5168 (2714)	3583 (2676)	2.38	0.02
N	35	32		

Note: The difference between full information and filtered information conditions is not significant. Therefore we pool these two groups and label it as "with information."

experimental studies on real options, e.g., Yavas & Sirmans (2005), Miller & Shapira (2004) and Howell & Jägle (1997). We use a continuous-time setting which more closely resembles how decisions are made in the real world. Although we did not recruit real managers for our tasks, our student subjects had mostly with economic or finance backgrounds, and were very interested in such management tasks. In a questionnaire at the end of the experiment, most participants indicated that they found the experiment interesting, and they also indicated maximizing payoffs is one of their main goals. Therefore, we believe the students were well motivated.

Although many people may believe managers and professionals are rational and can perform better than students and laymen, numerous empirical studies show that professionals also prone to various kinds of behavioral biases, e.g., Cadsby & Maynes (1998), Gort, Wang & Siegrist (2008), Shefrin (2007). It was also found in laboratory experiments that professional traders even perform worse than university students in the option pricing tasks (Abbink & Rockenbach 2006), and CEOs' behaved similarly to undergraduates in the bubble experiments (Ackert & Church 2001), etc. The behavioral biases found in our experiment, therefore, may not be unique only for undergraduate samples. The experimental and empirical studies are complementary in the sense that the observed behavior from well-controlled experiments offers us guidance regarding what kinds of behavioral biases we should look for when studying real-world decisions. The further step is to compare the behavioral patterns revealed in our experiment with the real-options investment behavior by professionals, and to study the implications of such biases on option pricing at the aggregate level through theoretical modeling.

Different types of investment behavior among players were identified using cluster analysis. We found that some participants' behavior closely resembled optimal real-option strategies, whereas others exhibited certain typi-

cal behavior biases. This is consistent with the general findings on “typing” heterogeneous behavior in dynamic decision problems. For example, in their experiment on Bayesian learning, El-Gamal & Grether (1995) identified Bayesians, conservative Bayesians, and those who used the representative heuristic. Houser, Keane & McCab (2004) classified their participants into “Nearly rational,” “Fatalist,” and “Confused.” Our results can shed light on understanding intuitive strategies people may adopt when it comes to real-option investment.

The first behavioral bias we noticed is the ignorance of a mean-reverting process. We elicited price expectation for each period, and it seems that most subjects believe in a mean-reverting price process. However, they did not incorporate this expectation into their decisions, and hence switched technologies as if they believed in a Brownian motion process, i.e., the expected future price is the same as the current price. Accordingly, they switched too often as compared with the theoretical benchmark when assuming a mean-reverting process. Although it is extremely difficult to determine the true process in reality, ignoring mean-reversion may undervalue the value of a project (Dixit & Pindyck 1994). In particular, not being able to incorporate the expected price process into decision making, as was the case among our participants, may be a more general behavioral bias that deserves further investigation.

Another bias we found is the insensitivity to the termination date. Nearly half of our participants played as if the game would last forever. They kept switching technologies till the end of the experiment, a strategy which would not pay off due to the high switching cost and low, limited expected profits.

However, some participants seemed to learn over time. There are two ways of learning in this game. One can learn to adopt a real-option approach while still assuming the Brownian motion process. Another possibility is to learn the true underlying mean-reverting process and incorporate this information into the decision making. We found the “Brownian motion real-option” group seemed to belong to the first case, whereas the “ambiguous” group seemed to learn in the second way. Future research should investigate how investors learn from their experience, and which conditions may help them learn faster.

In general, it seems that the real-option approach with a Brownian motion process makes more intuitive sense to most participants than the NPV approach, even though they leaned toward certain kinds of biases as described above. It is important to document the heterogeneity and understand which factors can cause such different behavior, an under-explored topic. Our study takes one further step in this direction, and we are planning more in-depth research on developing descriptive real-option theory, in order to understand

how managers learn, how they value information, and how they react to competition.

Acknowledgements

We thank Raphael Jordan, Tobias Ganz, and Maxim Litvak for technical supports on experiments and data analysis. Financial support from the National Centre of Competence in Research "Financial Valuation and Risk Management" (NCCR FINRISK), Project 3, "Evolution and Foundations of Financial Markets", the University Research Priority Program "Finance and Financial Markets" of the University of Zürich, and the Richard Büchner Foundation are gratefully acknowledged.

A Proof of Boundary Conditions

A.1 Geometric Brownian Motion

In the case of Geometric Brownian Motion, the dynamics of oil prices are given by:

$$\frac{dP_u}{P_u} = \sigma dW_u$$

where the constant parameter σ represents volatility. In this setting, the drift is equal to zero. The discount rate is the constant parameter r .

A.1.1 NPV approach

The expectation of the discounted profit Π_t corresponding to a switch in technology at time t (from the old one to a new one) is:

$$\mathbb{E}_{\mathbb{P}}(\Pi_t | \mathcal{F}_t) = (\mathbb{E}_{\mathbb{P}} \left[\int_t^T P_u e^{-r(u-t)} du \middle| \mathcal{F}_t \right] - C_{new}(T-t)) Q_{new} - I$$

where I represents the switching cost, from the old to the new technology, i.e.

$$\mathbb{E}_{\mathbb{P}}(\Pi_t | \mathcal{F}_t) = (\mathbb{E}_{\mathbb{P}} \left[P_t \int_t^T e^{-r(u-t)} e^{-\frac{\sigma^2}{2}(u-t) + \sigma(W_u - W_t)} du \middle| \mathcal{F}_t \right] - C_{new}(T-t)) Q_{new} - I$$

The experiment lasts only a few hours, therefore we assume that the interest rate r is equal to zero. In order to approximate the exercise boundary, we assume that the new technology will be kept until maturity T .

\mathbb{P} represents historical probability. The following result is obtained:

$$\mathbb{E}_{\mathbb{P}}(\Pi_t | \mathcal{F}_t) = Q_{new}(T-t)(P_t - C_{new}) - I$$

In order to obtain the critical price P^* , the expected discounted profit, in the case of technology change, has to be compared with the expected discounted profit if the firm keeps the old technology. Thus, this critical price satisfies the following equation:

$$Q_{new}(T-t)(P_t^* - C_{new}) - I = Q_{old}(T-t)(P_t^* - C_{old})$$

and expression 2 is obtained, with $\alpha = 1$. This case corresponds to the NPV approach.

A.1.2 The real option approach

In this setting, the players will wait longer before switching. Therefore we obtain a set of possible exercise boundaries:

$$\left\{ \frac{-\frac{\alpha I}{T-u} + Q_{old}C_{old} - Q_{new}C_{new}}{Q_{old} - Q_{new}} \middle| u \in [t, T], \alpha \geq 1 \right\}$$

which corresponds to expression 2. In order to derive the optimal parameter α^* , we rely on a Monte-Carlo simulation. The price process is simulated n times and we look for α which maximizes the average realized profit.

A.2 The Mean-Reverting process

In this case, we focus on an Orstein-Uhlenbeck process. The dynamics of oil prices are therefore given by:

$$dP_t = h(\mu - P_t)dt + \sigma dW_t$$

We work with the following utility function:

$$U(x) = ce^{cx}$$

where c is a negative parameter.

The expected utility of the profit Π_t corresponding to a switch in technology at time t is:

$$\mathbb{E}_{\mathbb{P}}(U(\Pi_t)|\mathcal{F}_t)$$

where:

$$\Pi_t = Q_{new} \left(\int_t^T P_u du - C_{new}(T-t) \right) - I$$

Therefore:

$$\begin{aligned}\mathbb{E}_{\mathbb{P}}(U(\Pi_t)|\mathcal{F}_t) &= \mathbb{E}_{\mathbb{P}}(e^{cQ_{new} \int_t^T P_u du}|\mathcal{F}_t) \times e^{-cC_{new}Q_{new}(T-t)} \times e^{-cI} \\ &= e^{cQ_{new}M(t,T)+\frac{c^2}{2}Q_{new}^2V(t,T)} \times e^{-cC_{new}Q_{new}(T-t)} \times e^{-cI}\end{aligned}$$

with:

$$\begin{aligned}M(t, T) &= \mu(T-t) + (P_t - \mu)\left(\frac{1 - e^{-h(T-t)}}{h}\right) \\ V(t, T) &= -\frac{\sigma^2}{2h^3}(1 - e^{-h(T-t)})^2 + \frac{\sigma^2}{h^2}\left(T-t - \frac{1 - e^{-h(T-t)}}{h}\right)\end{aligned}$$

Indeed, $\int_t^T P_u du$ is a normally distributed random variable with mean $M(t, T)$ and variance $V(t, T)$.

In order to obtain the exercise boundary, the expected utility of the profit with the new and the old technology has to be compared. P_t^* is the solution of the following equation:

$$\begin{aligned}e^{cQ_{new}M(t,T)+\frac{c^2}{2}Q_{new}^2V(t,T)}e^{-cC_{new}Q_{new}(T-t)-cI} &= \\ = e^{cQ_{old}M(t,T)+\frac{c^2}{2}Q_{old}^2V(t,T)}e^{-cC_{old}Q_{old}(T-t)-cI}\end{aligned}$$

i.e.

$$(Q_{old}-Q_{new})M(t, T) = -\frac{c}{2}(Q_{old}^2-Q_{new}^2)V(t, T)+(T-t)(Q_{old}C_{old}-Q_{new}C_{new})-I$$

$$\begin{aligned}(Q_{old}-Q_{new})(P_t-\mu)\left(\frac{1-e^{-h(T-t)}}{h}\right) &= -\frac{c}{2}(Q_{old}^2-Q_{new}^2)V(t, T)- \\ &\quad -I + (T-t)(Q_{old}C_{old}-Q_{new}C_{new})- \\ &\quad -(Q_{old}-Q_{new})\mu(T-t)\end{aligned}$$

i.e.

$$\begin{aligned}P_t^* &= \mu + \frac{h}{1-e^{-h(T-t)}}\left[-\frac{c}{2}(Q_{old}^2-Q_{new}^2)V(t, T)-I+ \right. \\ &\quad \left. + (Q_{old}C_{old}-Q_{new}C_{new})(T-t)-(Q_{old}-Q_{new})\mu(T-t)\right]/(Q_{old}-Q_{new})\end{aligned}$$

In the real option setting, there is a set of possible exercise boundaries:

$$\begin{aligned}\left\{\mu + \frac{h}{1-e^{-h(T-t)}}\left[-\frac{c}{2}(Q_{old}^2-Q_{new}^2)V(t, T)-\alpha I+ \right. \right. \\ \left. \left. + (Q_{old}C_{old}-Q_{new}C_{new})(T-t)-(Q_{old}-Q_{new})\mu(T-t)\right]\right\}/(Q_{old}-Q_{new}), u \in [t, T], \alpha \geq 1\end{aligned}$$

The exercise boundary corresponds to the value of α which maximizes the average realized profit. The NPV case is obtained for $\alpha = 1$.

A.3 The Brownian motion

In this case the dynamics of the underlying are given by:

$$dP_t = \sigma dW_t$$

The exercise boundary is obtained by letting h go to zero in the last equation. By relying on a Taylor expansion, we obtain the following set of possible exercise boundaries:

$$\left\{ \frac{(Q_{old}C_{old} - Q_{new}C_{new}) - \frac{\alpha I}{T-u} - \frac{c}{3}(Q_{old}^2 - Q_{new}^2)\sigma^2(T-t)^2}{Q_{old} - Q_{new}} \middle| u \in [t, T], \alpha \geq 1 \right\}$$

B Instruction sheet of the Experiment

Introduction

- This experiment investigates human behavior in the midst of uncertainty. The participants are rewarded according to their achievements.
- During the experiment, it is not allowed to communicate with other participants or to look at their screens.
- The experiment is to be processed to the full extent.
- If the participant does not follow the above rules, he or she will be disqualified from the experiment and not receive pay.

The structure of the experiment

- You play the role of the oil company manager and choose the technology which allows you to extract a certain quantity of oil and later sell it on the market.
- Each time period in the experiment corresponds to one day on the oil market. Overall, the experiment lasts 100 days.
- Every day you observe the price on the oil market. In the evening, after the market has closed, you will first be asked about your expectations regarding tomorrow. Only then can you decide on your production setup for the next day.
- You begin with the starting capital of \$3,000. If you go bankrupt, you will be fired and may no longer participate in the experiment. The higher wealth you achieved, the more you get paid.

Name	Cost per barrel	Production per day
Technology A	\$61.00	50 Barrel
Technology B	\$58.00	25 Barrel

- You can choose between 2 technologies with the following parameters:
- Every technology change incurs switching costs. A technology change costs \$350, a production stop costs \$300. If you start producing again with the same technology, you need to pay \$300, if you change technology after the stop, you need to pay \$350 for it.

Switching costs from A to B or from B to A	\$350
Switching costs from A to Stop or from B to Stop	\$300
Switching costs from Stop to the technology used before the Stop (e.g., A - Stop - A)	\$300
Switching costs from Stop to the technology different as one used before the Stop (e.g., A - Stop - B)	\$350

- The extracted oil is sold in the evening on the same day at the current price on the world market. Warning: there is no link here between reality and the experiment.
- During the game, you receive information on market trends which you need to work out.

Handling

- At the beginning, during the first 2 introductory periods, various information will be presented as well as how to run the software.
- On the next page you will find a screenshot with the statements on the relevant parts.

Examples of the performance calculation

1. At the beginning of the game a player starts production with technology A. After two periods he decides to stop production. At the end of two periods, the price of oil is \$56.40 and \$62.80 respectively. The profit is calculated as follows:

$$(\$56.4/\text{Barrel} - \$61/\text{Barrel}) * 50 \text{ Barrel} - \$0 = -\$230$$

$$(\$62.8/\text{Barrel} - \$61/\text{Barrel}) * 50 \text{ Barrel} - \$0 = \$90$$

2. The player then chooses to switch to technology B. With an oil price of \$66.40 at the 3-rd time period he/she earns:

$$(\$66.4/\text{Barrel} - \$58/\text{Barrel}) * 25 \text{ Barrel} - \$300 = -\$735$$

Initial wealth and pay-off calculation

- You take on the oil field with the following settings: Wealth: \$3,000, current technology: B.
- The pay-off depends on your performance. The more dollars you earn, the more money you receive. Your profit will be calculated as follows:

Total profit = Σ profits P_t of all time periods;

Profit of a time period $P_t = (\text{Oil price} - \text{Production costs}) * \text{Number of barrels produced} - \text{Switching costs}.$

- You receive a base salary of 10 CHF for your participation in the experiment. For every extra dollar you earn, you get 0.5 Rappen (i.e. \$1=CHF0.005). In case of loss, you don't have to pay anything back.
- The paid amount is rounded by CHF2.

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